Climate Predictions with imperfect models

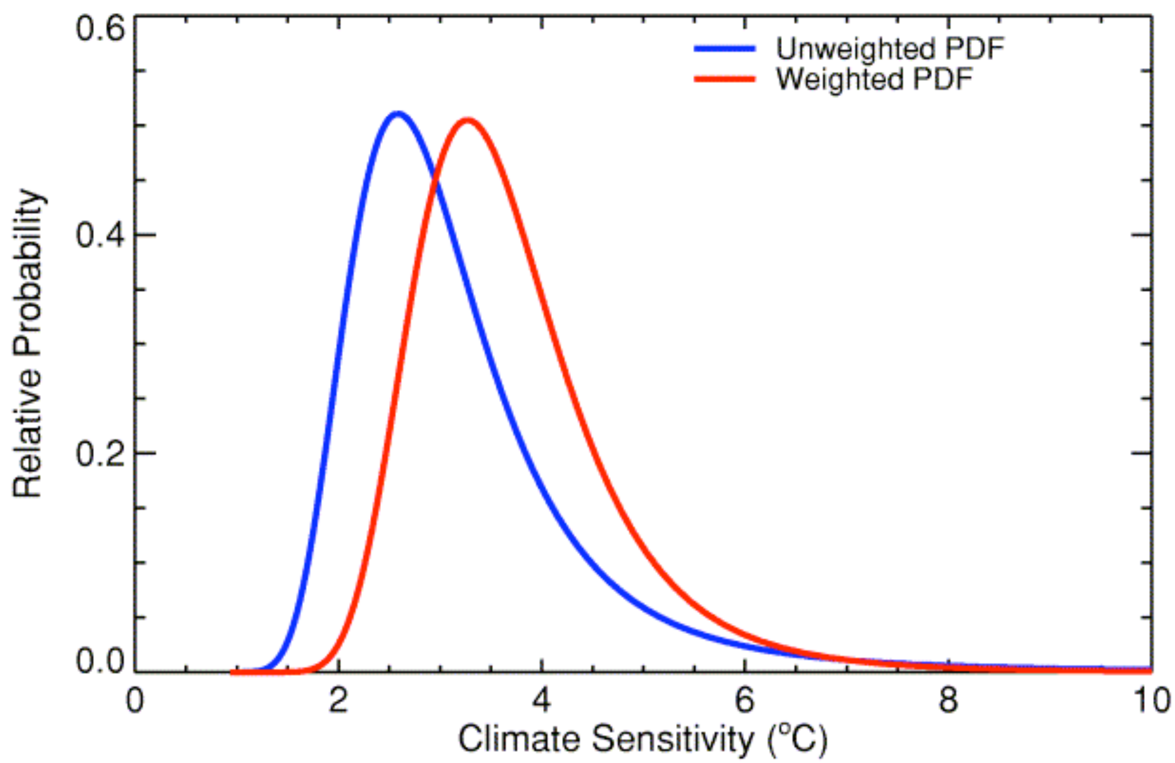
(“Hadley Centre QUMP”)

David Sexton

GERB-CERES workshop, 23-27 October, 2006

1. Introduction
2. Bayesian framework
3. Estimating model imperfection
4. Conclusions

Probabilistic predictions



Murphy et al 2004

Red curve calculated by weighting different parts of parameter space according to quality of simulation of present-day climate

What does probability distribution mean

- Could give policy-maker terabytes of model and observed data each time
- OR a summary statement of how future climate is consistent with the information provided
- Probability distribution is a function of
  - Model data
  - Observations
  - Prior information
  - Model imperfections
  - Analysis method and assumptions

Physics/dynamics matter…

- Compare models against several observational variables – with just one variable you can simulate climate well for the wrong reasons
- Will compare with present-day mean climate - Indirect assessment of key processes for our climate prediction but adds confidence to our prediction of one-off event
- We are not going to assume models are perfect so using better models has an impact

Bayesian framework

Bayesian prediction

- Aim is to construct joint probability distribution $p(X, m_h, m_f, y, o, d)$ of all uncertain objects in problem.
  - Input parameters (X)
  - Historical Model output (m_h)
  - Model prediction (m_f)
  - True climate (y_h,y_f)
  - Observations (o)
  - Model imperfections (d)
- It measures how all objects are related in a probabilistic sense

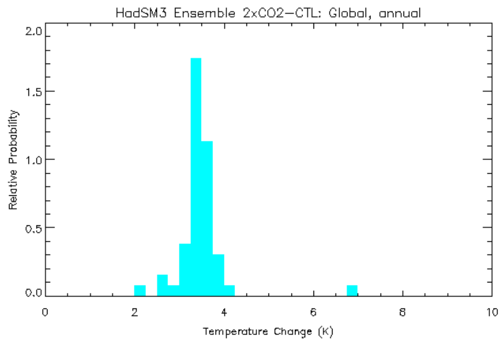
Goldstein and Rougier (2004) – The "Best-input" assumption

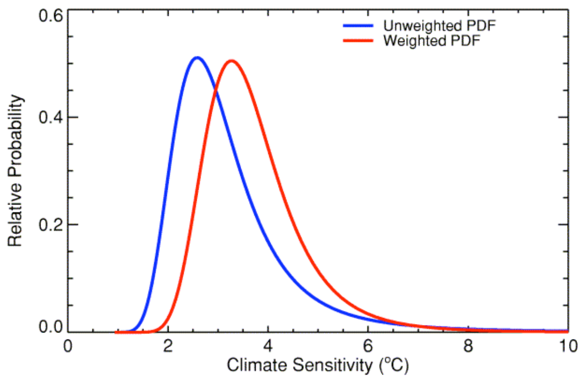
- Start with a perturbed physics ensemble
- Hypothesise that there is a set of input parameters, x*, that provide the best climate model
- But acknowledge that this best model is imperfect and that there is a discrepancy, d, compared to real climate
- We only know the probability that each point in parameter space is the best-input model. But that means we need a model at every part of parameter space…

Emulators

Emulators are statistical models, trained on ensemble of 300 slab runs, designed to predict model output at untried parameter combinations (a t-distribution at each sampled point)

Monte Carlo sampling of parameters combined with an emulator (combining lots of t-distributions) produces prior pdf (blue line).





Linking objects in Bayesian framework

Climate model

Discrepancy

True climate $$y = f(x^*) + \varepsilon$$

Emulator

Observations $$o = y_h + e$$

Model $$f(x) = \mu(x) + u(x)$$

$$o = \mu_h(x^*) + u_h(x^*) + \varepsilon_h + e$$

Emulator errror

Discrepancy

Obs error

Comparing models with observations

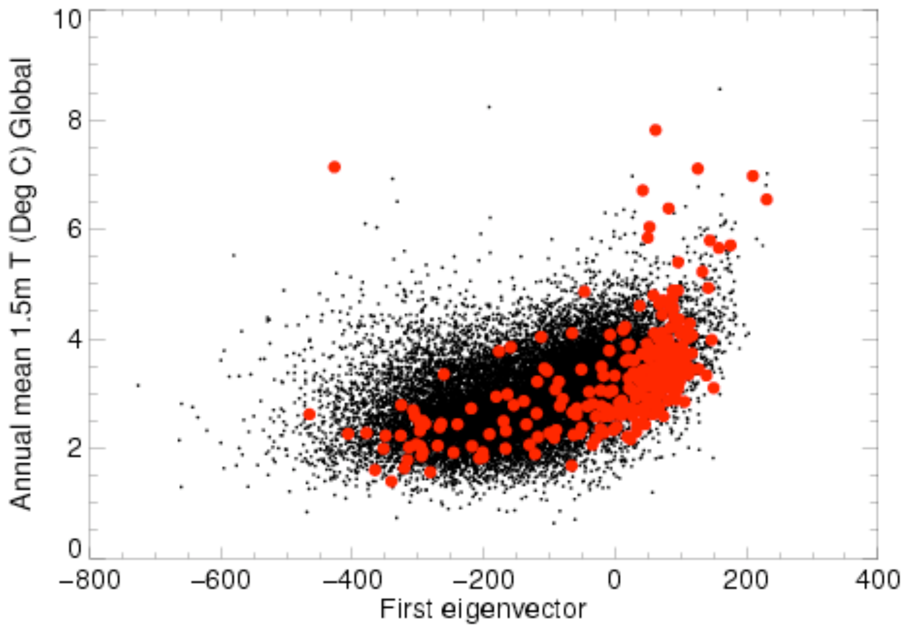
- Use likelihood function i.e. skill of model is likelihood of model data given some observations

$$\log L_o(\mathbf{m}) = -c - \frac{n}{2}\log|\mathbf{V}| - \frac{1}{2}(\mathbf{m}-\mathbf{o})^T \mathbf{V}^{-1}(\mathbf{m}-\mathbf{o})$$

V = obs uncertainty + emulator error + discrepancy

Constraining predictions

- Likelihood alters probability of x*
- Reduce uncertainty about the best input, x*



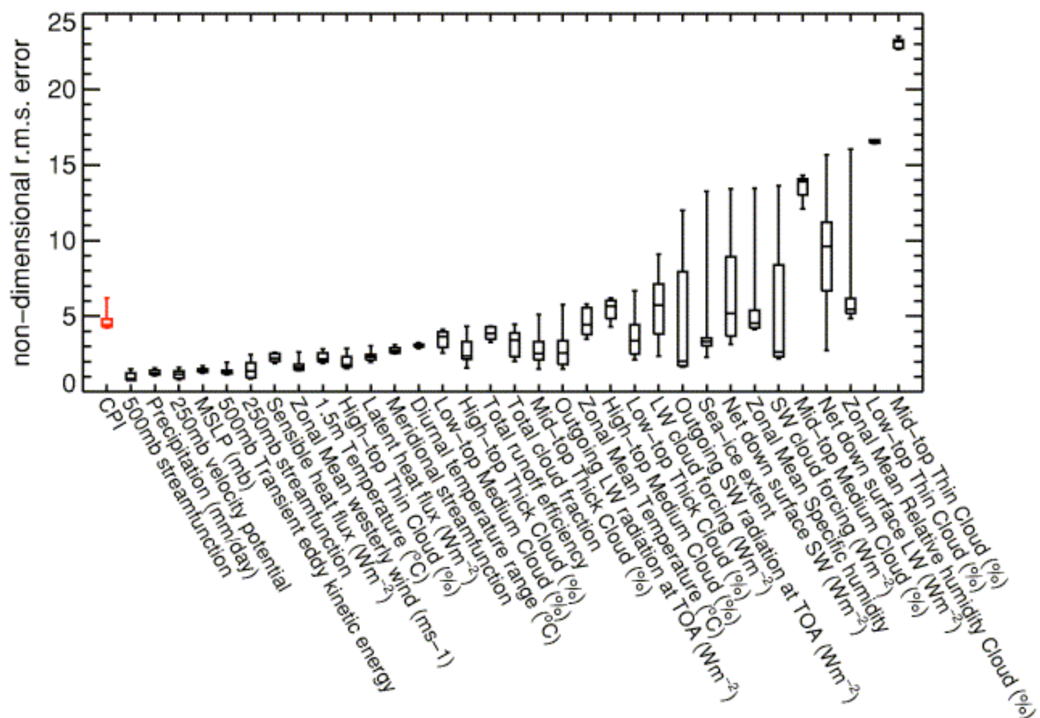
- Most effective if a strong relationship exists

Discrepancy on future variable

- Model not perfect so there are processes in real system not in our model that could alter model response by an uncertain amount.
- Places extra uncertainty on prediction variable in form of a variance

Discrepancy (ii)

- Avoids observations over-constraining the pdfs.
- Avoids contradictions from subsequent analyses when some observations have been allowed to constrain the problem too strongly.



Discrepancy (iii)

- Provides a means of accounting for model quality
  - Models with less imperfection given more weight – dynamics/physics matter!
  - Model improvements can subsequently be tracked
  - Constraint of observations gradually improve as model improves rather than jumping from “unusable” to “usable”.

Estimating a proxy for discrepancy

Estimating discrepancy

- Four ways I can think of…
  - Elicitation
  - Observations
  - Super-parameterised models
  - Ensemble of international climate models

Estimating discrepancy

- Use multimodel ensemble from AR4 and CFMIP
- For each multimodel ensemble member, find point in QUMP parameter space that is closest to that member
- There is a distance between climates of this multimodel ensemble member and this point in parameter space i.e. effect of processes not explored by QUMP.
- Pool these distances over all multimodel ensemble members

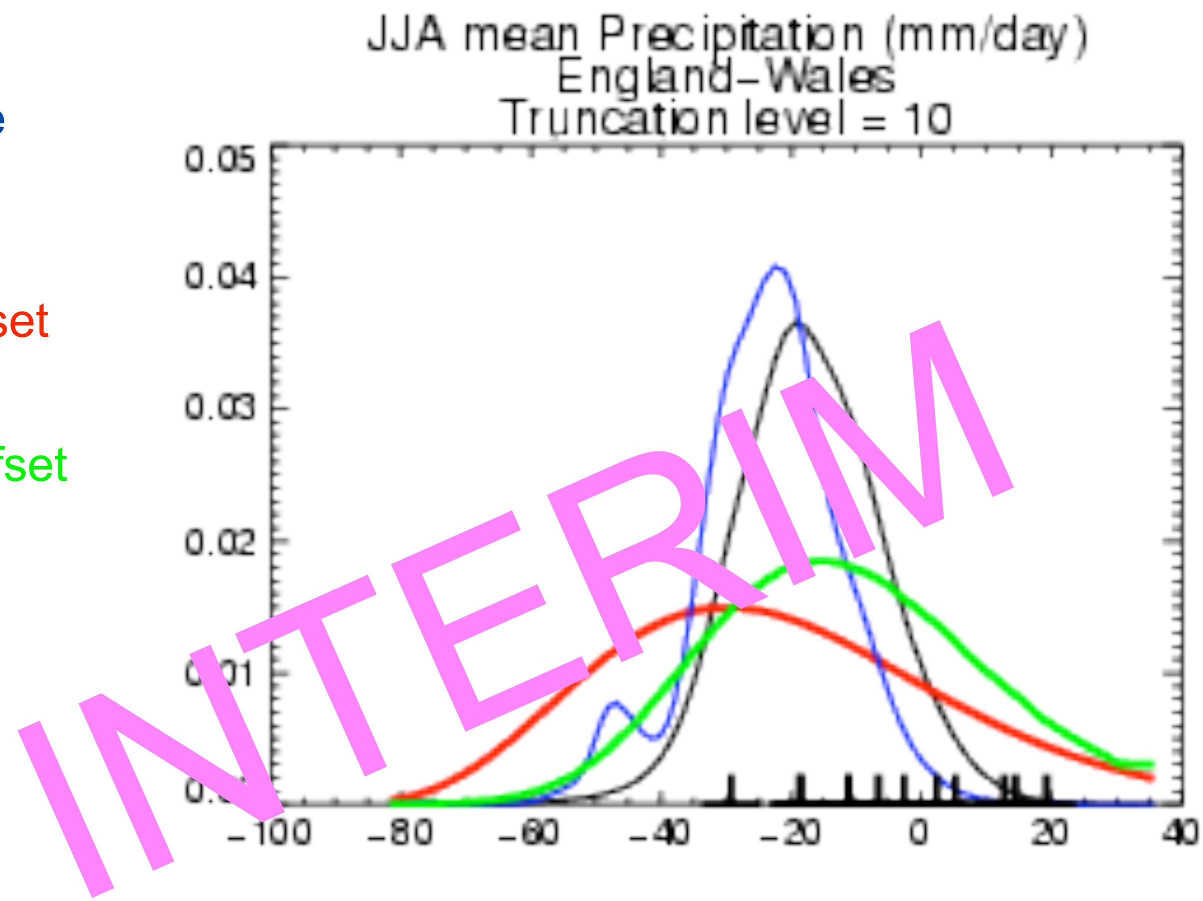
Adding information from other climate models e.g. summer UK rainfall

Prior

Posterior - no future discrepancy

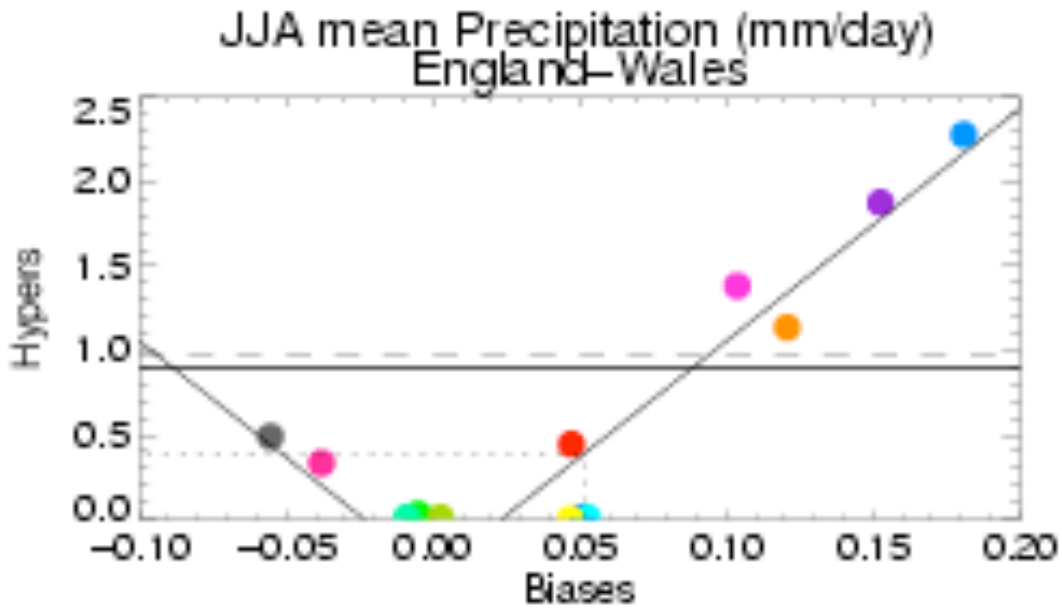
Posterior – future discrepancy, no offset

Posterior – future discrepancy with offset

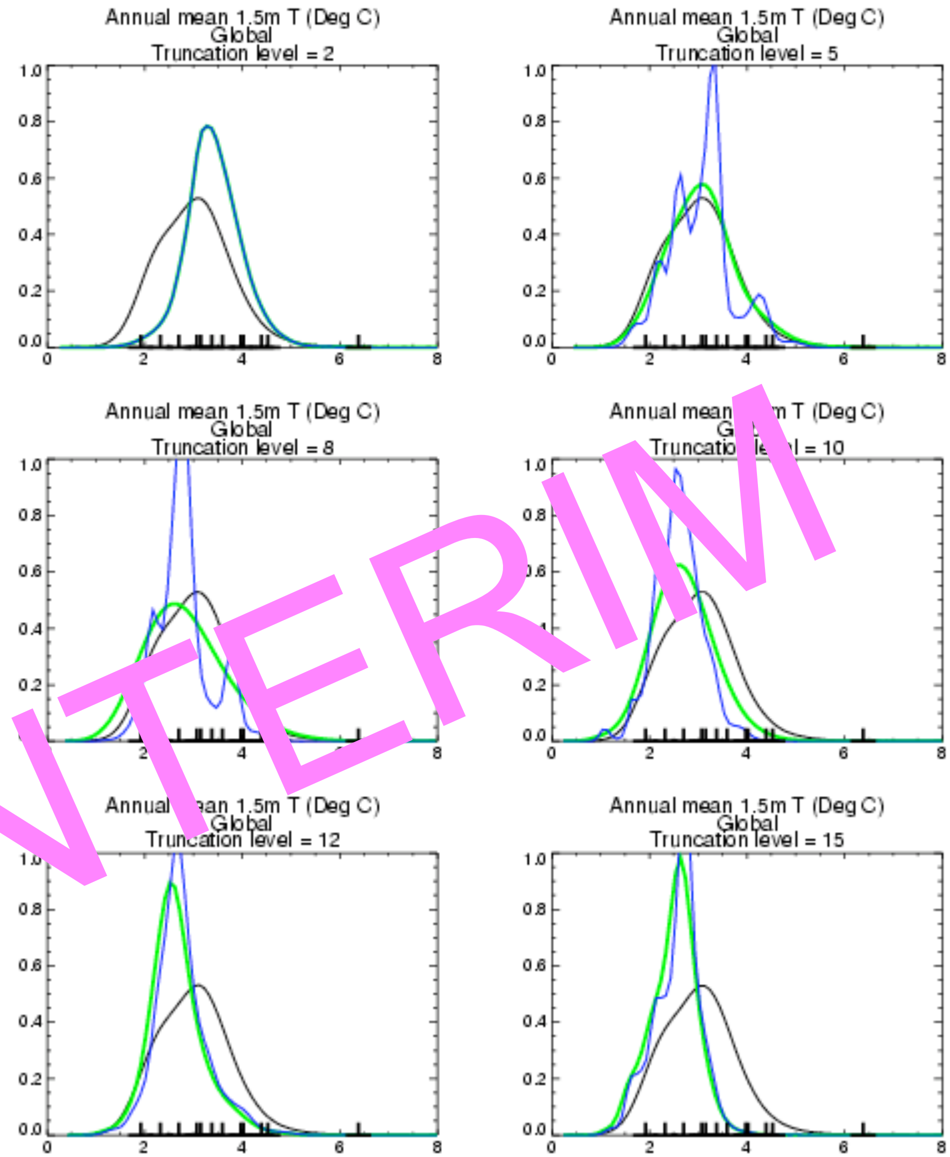


Biases in QUMP prediction of multimodel runs

X-axis is difference between each multimodel and its ‘best point’ in QUMP parameter space



Climate sensitivity



Conclusions

Properties of the climate prediction (i)

- MULTIVARIATE
  - Predicts joint distributions
    - Predictions of individual variables consistent with marginal distributions from joint analysis
    - Different prediction variables can be constrained by different observations
  - Can use lots of observations to constrain prediction
    - Only new independent observations impact on probability distribution

Properties of the climate prediction (ii)

- PRIOR
  - Don’t let predictions be dependent on sampling strategy
  - Instead predictions are representative of whole parameter space given some expert-chosen distribution
  - Allow a sensitivity analysis so it is easy to try out different expert’s distributions

Properties of the climate prediction (iii)

- MODEL IMPERFECTIONS
  - Acknowledge that our models are not perfect therefore we have to be careful about comparing modelled and observed data
    - Don’t let poorly modelled variables over-constrain PDF
  - Allow for a modelling uncertainty additional to one explored by perturbing parameters:
    - Observable model variables
    - Forecast variables

Reducing uncertainty

- Improve observational uncertainties
- Improve model i.e. reduce discrepancy
- Run larger ensembles
- Use more observational constraints independent of the ones used already

Observational uncertainties

- Please keep producing better data sets that allow the model to be evaluated in more detail
- Require observational errors in an easily-accessible format
- Any advice on errors for ERBE, CERES, or ISCCP most welcome.
- Any advice most welcome on new data sets and whether they need new model diagnostics.